Channel Estimation for Intelligent Reflecting Surface Enabled Terahertz MIMO Systems: A Deep Learning Perspective

Zhuoxun Li, Zhi Chen, Xinying Ma, and Wenjie Chen
University of Electronic Science and Technology of China, Chengdu 611731, China
Emails: zhuoxunliuestc@163.com; chenzhi@uestc.edu.cn; xymarger@126.com; wenjiechenuestc@163.com.

***Abstract*—Terahertz (THz) communications have been recognized as a promising technology to provide sufficient spectrum resources and ultra-high data rate for sixth generation (6G) wireless communication networks. To compensate the coverage hole caused by the propagation features of THz waves, an intelligent reflecting surface (IRS) is proposed to create the controllable propagation environment. However, the channel acquisition is particularly complicated for the IRS enabled THz multiple-input multiple-output (MIMO) system, since the IRS is lack of the signal processing capability. To this end, we firstly convert the channel estimation problem into a spare recovery problem by utilizing the sparsity nature of the THz channel. Then a deep learning based channel estimation (DL-CE) scheme is developed to solve the sparse recovery problem by revealing the relationship between the received signals and path gains. Simulation results demonstrate that, in contrast with classic compressed sensing based methods, our proposed DL-CE method achieves a better recovery performance and greatly decreases the computational complexity.**

***Index Terms*—Terahertz (THz) communications, intelligent reflecting surface (IRS), channel estimation, deep learning.**

I. Introduction

SIXTH generation (6G) wireless communication network has become a research focus to content the diverse application scenarios in the near further. One of the most important requirements is to develop new frequency bands. Fortunately, terahertz (THz) frequency band (from 0.1 THz to 10 THz) is envisioned as an appropriate choice to supply the large bandwidth and provide the sufficient spectrum resources [1]. Specifically, THz communication is able to realize extremely high transmission rates from hundreds of gigabit per second (Gbps) to several terabit per second (Tbps). When THz communication is applied to practical communication systems [2]. it still faces some challenges. Due to the strong directionality and high path attenuation of THz waves, the THz signals are easily blocked by the obstacles, such as walls, furniture, ceiling and so on. To tackle this issue, the intelligent reflecting surface (IRS) is newly proposed to settle the coverage problem as well as the spectral efficiency maximization problem [3]. To be specific, the IRS is a kind of physical meta-surface consisting of reflecting elements. Also, the phase shifts of IRS elements can be adjusted intelligently according to the variation of communication environment. Since the IRS is composed of many passive units without radio frequency (RF) chains, the hardware complexity and system consumption are very low, and thus more IRS elements can be scaled up in practice.

In order to guarantee the reliable THz communications, the channel state information (CSI) needs to be acquired firstly. Nevertheless, the main difficulty is that the IRS lacks active RF chains as well as the sensing capability. To this end, the work in [4] proposes a novel IRS hardware structure, in which all the reflecting elements are passive except several randomly distributed active reflecting elements. Such an architecture can handle the channel estimation problem with low training overhead, but on the contrary, designing partial active channel sensors within passive IRS elements definitely increases extra hardware complexity and power consumption. In [5], a binary-reflection (full or no) controlled least channel estimation protocol for downlink multiple-input single-output (MISO) systems, considering that an IRS does not involve any active components. But this proposed scheme needs to estimate all the channel vectors one-by-one and leads to high system latency. Interestingly, the authors attempt to solve the cascaded channel estimation problem for the IRS-assisted multiple-input multiple-output (MIMO)systems by utilizing a two-stage algorithm that contains a sparse matrix factorization stage and a matrix completion stage [6]. Nevertheless, the channel features (e.g., sparsity, path loss) of this communication system working at THz frequency band are not taken into consideration. Prominently, the authors convert the channel estimation problem into the spare signal recovery problem by leveraging the sparse nature of THz MIMO channel. Then, a low complexity compressed sensing (CS) based channel estimation scheme is developed to realize the efficient signal reconstruction [7]. Since the IRS at THz frequency band owns immense reflecting elements, the CSI acquisition schemes mentioned above suffer from intolerable calculation burden. Hence, the low complexity channel estimation scheme is worthy of further exploration.

In this paper, we firstly formulate the channel estimation problem as the sparse recovery problem for a downlink IRS assisted THz MIMO communication system. Based on this model, an efficient deep learning based channel estimation (DL-CE) scheme is proposed, which employs the two-stage

This work is supported by the National Key Research and Development Project of China (No.2018YFB1801500).

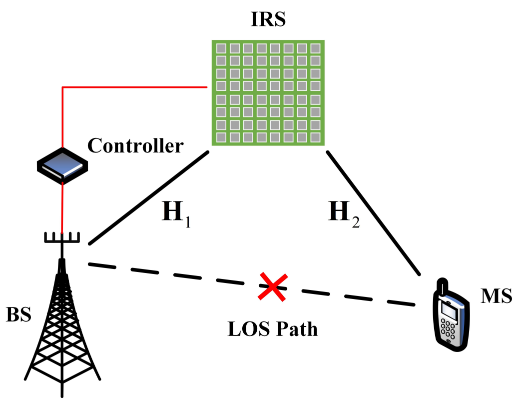

Fig. 1. Illustration of the IRS-enabled THz MIMO system.

neural network to settle the sensing matrix design and the signal reconstruction simultaneously. More specifically, for the first stage, our proposed neural network mimics the noisy linear measurement process and reveals the relationship among the received pilot vector, sensing matrix and the sparse signal vector. For the second stage, the sparse recovery function is characterized by our proposed neural network, which accomplishes the sparse signal reconstruction process. According to neural network architecture, our developed DL-CE scheme is able to realize a much better recovery performance while possesses lower computational complexity compared with conventional compressed sensing based schemes.

II. System Model and Problem Formulation

In this section, the IRS-assisted THz MIMO communication model is introduced firstly. Then, the sparse recovery problem of the channel estimation is formulated.

A. System Model

We consider a downlink IRS assisted THz MIMO communication system, as shown in Fig. 1. In detail, a base station (BS) with N_{BS} antennas and M_{BS} RF chains a single mobile station (MS) with N_{MS} antennas and M_{MS} RF chains. Between the BS and the MS, an IRS is installed to compensate for the severe path attenuation at THz band, which consists of N_{IRS} passive reflecting elements. In order to obtain the desired phase information by the IRS, a controller is configured in this system connecting the IRS and the BS. In general, the line-of-sight (LOS) path is usually blocked by the obstacles (e.g., wall, door, furniture). Thus, the non-line-of-sight (NLOS) paths is regarded as the main communication links.

When we consider the total P time frames and the MS employs the same combiner $\mathbf{W} \in \mathcal{C}^{N_{\mathrm{MS}} \times Q}$ to detect the incoming signals, the received signal matrix at the MS can be written as [7]

$$\mathbf{Y} = \mathbf{W}^H \mathbf{H} \mathbf{X} + \mathbf{Z}, \tag{1}$$

where $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, \cdots, \mathbf{y}_P]$ is a $Q \times P$ received matrix, $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_P]$ is a $N_{\mathrm{BS}} \times P$ hybrid beamforming matrix, $\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \cdots, \mathbf{z}_P]$ is a $Q \times P$ noise matrix by concatenating the P noise vectors, respectively.

Preceding with the sparse channel estimation problem, the channel model for the IRS-enabled MIMO THz communication system needs to be described here. Differing from the conventional MIMO channel [8], the IRS-based THz MIMO channel model is composed of the BS-IRS channel $\mathbf{H}_1$, the IRS-MS channel $\mathbf{H}_2$, and the phase shift matrix $\boldsymbol{\Phi} = \mathrm{diag}\left(\left[e^{j\varphi_1}, \cdots, e^{j\varphi_{N_{\mathrm{IRS}}}}\right]^T\right)$, where $\boldsymbol{\Phi}$ is a $N_{\mathrm{IRS}} \times N_{\mathrm{IRS}}$ diagonal matrix to indicate the phase shifts of IRS elements. According to the components of channel, the whole channel of the IRS enabled system can be expressed as

$$\mathbf{H} = \mathbf{H}_2 \boldsymbol{\Phi} \mathbf{H}_1. \tag{2}$$

One may note that, at THz frequency band, both $\mathbf{H}_1$ and $\mathbf{H}_2$ are able to be presented by the geometric channel model with few scattering paths. In light of the geometric channel model, the BS-IRS channel $\mathbf{H}_1$ can be formulated as

$$\mathbf{H}_1 = \sqrt{\frac{N_{\mathrm{BS}} N_{\mathrm{IRS}}}{L_1}} \sum_{l_1=1}^{L_1} \alpha_{l_1} \mathbf{a}_{\mathrm{IRS}}(\gamma_{l_1}^{\mathrm{AOA}}) \mathbf{a}_{\mathrm{BS}}^H(\phi_{l_1}), \tag{3}$$

where L_1 denotes the number of the scattering paths for the BS-IRS link, α_{l_1} is the complex path gain of l_1th path, $\gamma_{l_1}^{\mathrm{AOA}} \in [0, 2\pi]$ is the AoA and $\phi_{l_1} \in [0, 2\pi]$ is the AoD of l_1th path corresponding to $\mathbf{H}_1$. The complex gains of the propagation paths are mainly influenced by the path loss and molecular absorption, and more details are recommended in [9]. In addition, the uniform linear arrays (ULAs) are considered here. Hence,the array response vectors $\boldsymbol{a}_{\mathrm{BS}}(\phi_{l_1})$ and $\boldsymbol{a}_{\mathrm{IRS}}(\gamma_{l_1}^{\mathrm{AOA}})$ can be written as

$$\begin{aligned}\mathbf{a}_{\mathrm{BS}}(\phi_{l_1}) = \tfrac{1}{\sqrt{N_{\mathrm{BS}}}} \Big[1, e^{j(2\pi/\lambda) d \sin(\phi_{l_1})}, \cdots \\ , e^{j(N_{\mathrm{BS}}-1)(2\pi/\lambda) d \sin(\phi_{l_1})}\Big]^T,\end{aligned} \tag{4}$$

$$\begin{aligned}\mathbf{a}_{\mathrm{IRS}}(\gamma_{l_1}^{\mathrm{AOA}}) = \tfrac{1}{\sqrt{N_{\mathrm{IRS}}}} \Big[1, e^{j(2\pi/\lambda) d \sin(\gamma_{l_1}^{\mathrm{AOA}})}, \cdots \\ , e^{j(N_{\mathrm{IRS}}-1)(2\pi/\lambda) d \sin(\gamma_{l_1}^{\mathrm{AOA}})}\Big]^T,\end{aligned} \tag{5}$$

where λ is the wavelength of the THz waves and d is the distance between adjacent antennas or IRS elements, which is usually defined as $d = \lambda/2$. Except for the normal form (3), a more compact form of channel $\mathbf{H}_1$ can be expressed as

$$\mathbf{H}_1 = \mathbf{A}_{\mathrm{IRS},1} \mathrm{diag}(\alpha) \mathbf{A}_{\mathrm{BS}}^H, \tag{6}$$

where $\boldsymbol{\alpha}{=}\sqrt{N_{\mathrm{BS}} N_{\mathrm{IRS}}/L_1}[\alpha_1, \alpha_2, \cdots, \alpha_{L_1}]^T$, and the array response matrices can be respectively given as

$$\mathbf{A}_{\mathrm{BS}} = [\mathbf{a}_{\mathrm{BS}}(\phi_1), \cdots, \mathbf{a}_{\mathrm{BS}}(\phi_{L_1})], \tag{7}$$

$$\mathbf{A}_{\mathrm{IRS},1} = \left[\mathbf{a}_{\mathrm{IRS}}(\gamma_1^{\mathrm{AOA}}), \cdots, \mathbf{a}_{\mathrm{IRS}}(\gamma_{L_1}^{\mathrm{AOA}})\right]. \tag{8}$$

Similar to the BS-IRS channel $\mathbf{H}_1$, the IRS-MS channel $\mathbf{H}_2$ can be obtain as

$$\mathbf{H}_2 = \mathbf{A}_{\mathrm{MS}} \mathrm{diag}(\boldsymbol{\beta}) \mathbf{A}_{\mathrm{IRS},2}^H, \tag{9}$$

where

$$\begin{aligned}&\boldsymbol{\beta}=\sqrt{N_{\mathrm{MS}}N_{\mathrm{IRS}}/L_2}[\beta_1,\beta_2,\cdots,\beta_{L_2}]^T,\\&\mathbf{A}_{\mathrm{MS}}=[\mathbf{a}_{\mathrm{MS}}(\theta_1),\cdots,\mathbf{a}_{\mathrm{MS}}(\theta_{L_2})],\\&\mathbf{A}_{\mathrm{IRS},2}=\left[\mathbf{a}_{\mathrm{IRS}}(\gamma_1^{\mathrm{AOD}}),\cdots,\mathbf{a}_{\mathrm{IRS}}(\gamma_{L_2}^{\mathrm{AOD}})\right],\end{aligned}\tag{10}$$

By combining (6) and (9), the entire channel model can be rewritten as

$$\mathbf{H}=\mathbf{A}_{\mathrm{MS}}\mathrm{diag}(\boldsymbol{\beta})\mathbf{A}_{\mathrm{IRS},2}^H\boldsymbol{\Phi}\mathbf{A}_{\mathrm{IRS},1}\mathrm{diag}(\boldsymbol{\alpha})\mathbf{A}_{\mathrm{BS}}^H.\tag{11}$$

B. Problem Formulation

For the sake of formulating the sparse channel estimation problem, we discard the grid quantization process existing CS-based schemes [7], and directly vectorize the received matrix $\mathbf{Y}$ in (1). Thus, the vectorized received signal $\mathbf{y}_v$ can be represented as

$$\begin{aligned}\mathbf{y}_v&=\mathrm{vec}\left(\mathbf{Y}\right)\\&=\left(\mathbf{X}^T\otimes\mathbf{W}^H\right)\mathrm{vec}\left(\mathbf{H}\right)+\mathrm{vec}\left(\mathbf{Z}\right).\end{aligned}\tag{12}$$

We define that $\mathbf{U}=diag(\boldsymbol{\alpha})$ and $\mathbf{V}=diag(\boldsymbol{\beta})$. By continuing to vectorize (12), the sparse recovery problem can be formulated as

$$\begin{aligned}\mathbf{y}_v=&\left(\mathbf{X}^T\otimes\mathbf{W}^H\right)\left[\left(\left(\mathrm{vec}\left(\boldsymbol{\Phi}\right)\right)^T\left(\mathbf{A}_{\mathrm{IRS},1}\otimes\mathbf{A}_{\mathrm{IRS},2}^*\right)\right)\right.\\&\left.\otimes\left(\mathbf{A}_{\mathrm{BS}}^*\otimes\mathbf{A}_{\mathrm{MS}}\right)\right]\mathrm{vec}\left(\mathbf{U}^T\otimes\mathbf{V}\right)+\mathrm{vec}\left(\mathbf{Z}\right)\\=&\mathbf{A}_v\mathbf{x}_v+\mathbf{z}_v\end{aligned},\tag{13}$$

where $\mathrm{vec}(\cdot)$ represents the vectorization operation, $\mathbf{A}_v$ is observed as a $PQ\times L_1^2L_2^2$ sensing matrix, $\mathbf{x}_v=\mathrm{vec}\left(\mathbf{U}^T\otimes\mathbf{V}\right)$ is a $L_1^2L_2^2\times 1$ sparse signal vector and $\mathbf{z}_v=\mathrm{vec}\left(\mathbf{Z}\right)$ is a $PQ\times 1$ vectorized noise vector, respectively. According to (13), the spare reconstruction problem is formulated, and the main target is to recover the sparse signal $\mathbf{x}_v$. Once $\mathbf{x}_v$ is obtained, the mixed $\mathbf{U}$ and $\mathbf{V}$ can be separated on account of the special communication conditions [7].

III. Proposed Deep Learning Based Channel Estimation Scheme

With regard to the sparse recovery problem (13) of the IRS-enabled THz MIMO system, the CS-based channel estimation scheme is treated as a simple and effective approach [7]. However, the CS-based method involves extremely high computational complexity due to the double grid quantization operation. To this end, we propose a low complexity DL-CE scheme to solve the sparse recovery problem directly, which is composed of two-stage neural network(NN) and hard threshold module. Specifically, the two-stage NN consists of the first-stage that simulates the linear measurement process of received signal, and the second stage approximately performs sparse support recovery from the under sampled linear measurements.

A. Two-stages NN

First of all, we introduce the training data sets which consist of $\mathbf{x}$, sensing matrix $\mathbf{A}$ and $\hat{\mathbf{x}}$, as shown in Fig. 2. Note that $\hat{\mathbf{x}}$ represents the recovered signal vector $\mathbf{x}$. And in this paper, we construct the training sets consist of I training samples $\left(\mathbf{x}^{(i)},\hat{\mathbf{x}}^{(i)}\right),i=1,\cdots,I$. We note that the NN is non-linear technique that finds an approximate solution by defining a cost function. This cost function is controlled by a set of adaptive parameters. At present, the standard NN can only deal with real numbers. However, in many application scenarios, the sparse recovery process involves complex number. To solve this problem, we introduce a two-stages NN architecture which can deal with complex number by simulating the the linear measurement of received signal in this part. Thus, the complex equations can be expressed by two real number equations as

$$\begin{aligned}\Re(\mathbf{y})=\Re(\mathbf{A})\Re(\mathbf{x})-\Im(\mathbf{A})\Im(\mathbf{x})+\Re(\mathbf{z})\\\Im(\mathbf{y})=\Im(\mathbf{A})\Re(\mathbf{x})-\Re(\mathbf{A})\Im(\mathbf{x})+\Im(\mathbf{z})\end{aligned}\tag{14}$$

where $\Re(\cdot)$ and $\Im(\cdot)$ represent the real part and imaginary part of a complex number. Based on (14), we establish two completely correlated perceptrons, each of which has two layers. Furthermore, through the first stage, two linear relationships are simulated by coefficient matrix $\Re(\mathbf{A})$ and $\Im(\mathbf{A})$, respectively. For each perceptron which has S neurons in the input layer and P neurons in the output layer, doesn't use nonlinear activate functions in consideration that aiming to simulate linear function. For fully connected networks, all the weights of the connection from the S neurons in the input layer to the P neurons in the output layer can structure the weight matrix $\mathbf{W_0}\in R^{S\times D}$ ($\mathbf{W_0}=\Re\left(\mathbf{A}\right)or\Im\left(\mathbf{A}\right)$). As showed in fig, the outputs $\Re(\mathbf{A})\Re(\mathbf{x})$ and $\Re(\mathbf{A})\Im(\mathbf{x})$ (or $\Im(\mathbf{A})\Re(\mathbf{x})$ and $\Im(\mathbf{A})\Im(\mathbf{x})$)can be obtained through the linear processing between the inputs $\Re(\mathbf{x})$ and $\Im(\mathbf{x})$ and the weight matrices $\Re(\mathbf{A})$ (or $\Im(\mathbf{A})$). According to [10], $\Re(\mathbf{y})$ and $\Im(\mathbf{y})$ can be calculated and input in the second-stage.

Then, the second stage NN is described which approximate sparse support recovery for the sparse channel gains. On the basis of the working principle of the neural network, the input value for each current neural unit sums the product of the output values from the previous layer and the corresponding weights. In the hidden layers, Sigmoid function($Sigmoid(x)=\frac{1}{1+e^{-x}}$) is chosen to process the summation values aiming to mimic the nonlinear relations and alleviate gradient dissipation problems. Then, the output values of current neural units can be further utilized for the next layer. According to the principle, we establish a fully connected neural network with five layers: one input layer, three hidden layers and one output layer. The input layer has $2L$ neurons, of which the first L cells are the real part of $\mathbf{y}$ and the last L cells are the imaginary part of $\mathbf{y}$. Each of the three hidden layers has E neurons and takes the Sigmoid function as the activation function. It should be noted that in the output layer, there are N cells which are processed by Sigmoid function and normalization to guarantee the output values are not too big. Since the purpose of sparse recovery is to find the channel gains of sparse efficient paths, in order to facilitate processing and reduce the error rate, we normalize the output data to $[0,30]$, so as to facilitate subsequent judgment.

To represent four weight matrices between 5 layers of the second-stage, matrices $\mathbf{W_1}\in\mathbf{R}^{2D\times E},\mathbf{W_2}\in\mathbf{R}^{E\times E},\mathbf{W_3}\in\mathbf{R}^{E\times E}$ and $\mathbf{W_4}\in\mathbf{R}^{E\times N}$ are defined to storage the weights of the connections of every two layers. Beside, vectors

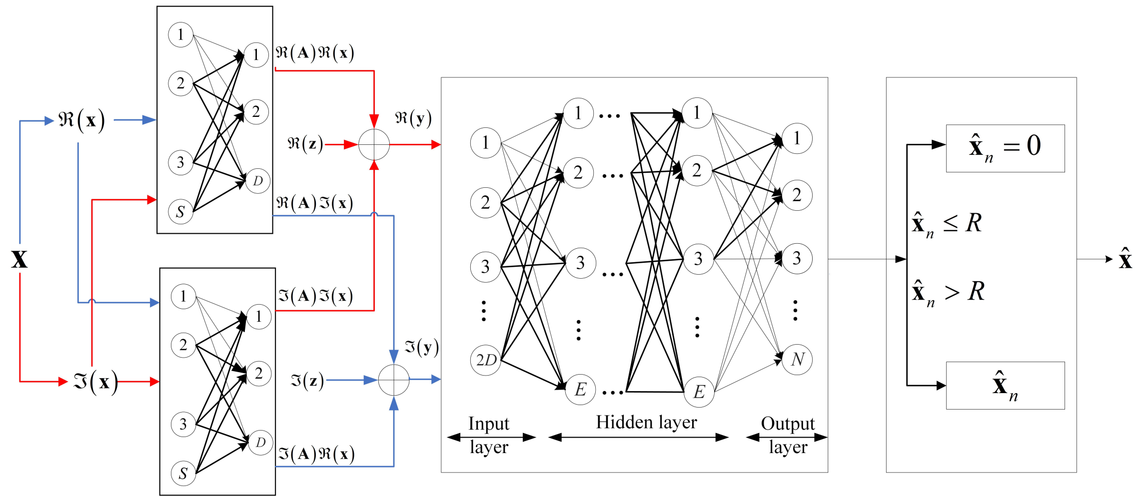

Fig. 2. Proposed neural network architecture for channel estimation.

$\mathbf{b}_1 \in \mathbf{R}^E, \mathbf{b}_2 \in \mathbf{R}^E, \mathbf{b}_3 \in \mathbf{R}^E$ and $\mathbf{b}_4 \in \mathbf{R}^N$ are used to denote bias values corresponding to the three hidden layers and the output layer, respectively. In summary, we define the coefficient matrix $\mathbf{G} \triangleq ((\mathbf{W}_i, \mathbf{b}_i))_{i=1,2,3}$ to storage all the parameters of the second-stage NN.

During the training process of the second-stage NN, we need to minimize the regression loss function until the proposed NN converges. So as to measure the distance between $\hat{\mathbf{x}}^{(i)}$ and $\mathbf{x}^{(i)}$, the loss function $L(\mathbf{W}, \mathbf{A})$ is expressed as:

$$L(\mathbf{G}, \mathbf{A}) = \frac{1}{LI} MMSE \left(\sum_{i=1}^{i=I} (\hat{\mathbf{x}}^{(i)} - \mathbf{x}^{i}) \right) \tag{15}$$

Adaptive momentum(Adam) algorithm which is a first-order gradient based optimization algorithm for random objective function, is utilized in this paper to train second-stage NN. After the entire two-stages NN model is trained, the sparse channel gains are known, whose position can help us extract the corresponding symbols in the sensing matrix dictionary to form the corresponding sensing matrix.

B. Hard Thresholding Module

Considering the sparsity of the input channel gain, there should be many 0 elements in the output vector of the second layer neural network, but there are errors in the data processing of the neural network. Maybe many elements of the final output vector are small values but not 0. In order to solve this problem, we design a hard decision module controlled by threshold R to select the best gain value. And the criteria are as follows:

$$\hat{\alpha}_i = \begin{cases} 0, r \le R \\ \alpha_i, r > R \end{cases}, i = 1, 2, \cdots M \tag{16}$$

where $\hat{\alpha}_i$ represent the ith element of the output vector $\hat{\alpha}$. R is the specific value of the threshold which is calculated by $R = \frac{1}{I} \sum_{i=1}^{i=I} I_i$

IV. Numerical Results

In this section, numerical results are described to demonstrate the average error rate and complexity of the proposed data-driven scheme and baseline schemes over the same set of testing data sets for the IRS-aided THz MIMO system. For a downlink communication scenario, we assume the BS with $N_{\text{BS}} = 128$ antennas serves the MS with $N_{\text{MS}} = 32$ antennas. Also, we assume the number of IRS elements is $N_{\text{IRS}} = 32$, where the number of quantization bits is 2 and the working frequency is at 0.34 THz. The maximization epochs, learning rate and batch size in training the proposed architecture are set as 10000, 0.001 and 128, respectively. When the value of the loss function on the validation set does not change for five epoches, the training process is stopped and the corresponding parameters of the auto-encoder are saved. Note that in this paper, the average error rate under test data sets can be described as

$$NMSE(\hat{\alpha}) = \frac{1}{S} \sum_{i=1}^{i=S} \frac{\|\hat{\boldsymbol{\alpha}}_i - \mathbf{x}\|_2^2}{\|\mathbf{x}\|_2^2} \tag{17}$$

where $S = 1000$ is the number of test data sets.

A. Average Error Rate Comparison

Fig. 3 depicts the average error rate of our proposed channel recovery methods with different signal to noise ratio (SNR) values. From Fig. 3 we can see that, with the increasing number of SNR, the average error rate of the DL-CE scheme gradually decreases. Specifically, when the SNR is set as 30 dB, the average error rate of our proposed channel estimation scheme is about 7.1%. It is worth noting that much better recovery performance can be achieved by improving the SNR level of the IRS-enabled THz system.

Fig. 4 illustrates the average error rate performance of our proposed DL-CE scheme with the increasing number of paths. In particular, the number of the propagation paths means the number of the BS-IRS channel paths L_1 and the number of

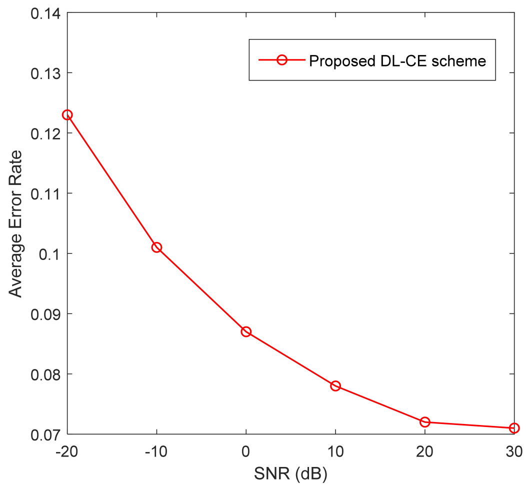

Fig. 3. Average error rate versus SNR.

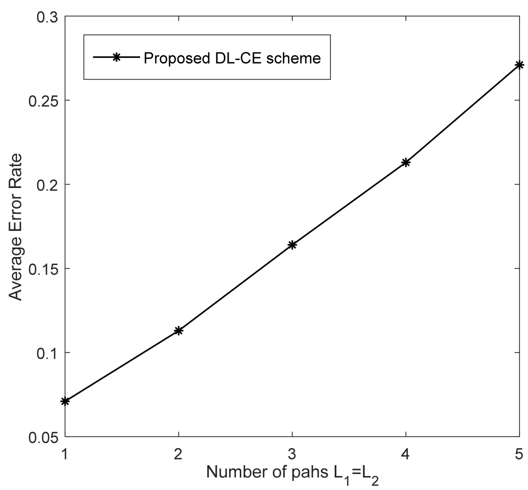

Fig. 4. Average error rate versus the number of paths $L_1 = L_2$.

the IRS-MS channel paths L_2. As shown in Fig. 4, the average error rate for DL-CE scheme increases with the growth of the number of paths. In other words, the more sparse the THz channel is, the better the signal recovery performance is. When the number of the paths $L_1 = L_2 = 3$, the average error rate is about 0.16. Fig. 4 also indicates that our proposed DL-CE scheme can make full use of the sparse nature of the THz channel.

B. Complexity Analysis

Without loss of generality, the computational complexity of the offline training can be ignored, and thus the major calculation burden of our proposed DL-CE scheme comes from the online operation. Based on the algorithm procedure of our proposed neural network model, the complexity of online predictions mainly involves the operations of multiplying the output value of each unit with the corresponding weight. Therefore, the complexity between two layers is the product of the input vector and the weight matrix. In terms of the auto-encoder architecture, the total complexity of the proposed scheme can be determined as:

$$\mathcal{O}_{DD}\left(2SP + 2PQ + 4Q^2 + QN + 4LQ\right) \tag{18}$$

where L the number of paths $L = L_1 + L_2$. Obviously, the complexity is reduced by several orders of magnitude. From (18) we can see that our proposed DL-CE scheme possesses extremely low complexity and can be well applied to the practical communication scenarios.

V. Conclusion

In this paper we first attempt to settle the channel estimation problem for the IRS enabled THz MIMO system from a deep learning perspective. In addition, we convert the channel estimation problem into the sparse recovery problem by utilizing the sparse nature of the THz channel. Then we develop a DL-CE scheme to jointly design the measurement matrix and support recovery method for the complex sparse signals with low complexity. The proposed DL-CE scheme opens the completely new research interests of the channel estimation for the IRS-enabled THz MIMO communications.

References

[1] Z. Chen, X. Y. Ma, B. Zhang, et al., "A survey on terahertz communications," *China Communications*, vol. 16, no. 2, pp. 1-35, Feb. 2019.

[2] I. F. Akyildiz, J. M. Jornet, and C. Han, "Terahertz band: Next frontier for wireless communications," *Physical Communication (Elsevier)*, vol. 12, no. 4, pp. 16-32, 2014.

[3] X. Ma, Z. Chen, W. Chen, et al., "Intelligent reflecting surface enhanced indoor terahertz communication systems," *Nano Communication Networks*, vol. 24, pp. 100284, May. 2020.

[4] A. Taha, M. Alrabeiah, and A. Alkhateeb, Enabling large intelligent surfaces with compressive sensing and deep learning, [Online]. Available: arXiv:1904.10136, 2019.

[5] D. Mishra and H. Johansson, "Channel Estimation and Low-complexity Beamforming Design for Passive Intelligent Surface Assisted MISO Wireless Energy Transfer," *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 4659-4663, 2019.

[6] Z. He and X. Yuan, "Cascaded Channel Estimation for Large Intelligent Metasurface Assisted Massive MIMO," *IEEE Wireless Communications Letters*, vol. 9, no. 2, pp. 210-214, Feb. 2020.

[7] X. Ma, Z. Chen, W. Chen, et al., "Joint Channel Estimation and Data Rate Maximization for Intelligent Reflecting Surface Assisted Terahertz MIMO Communication Systems," *IEEE Access*, vol. 8, pp. 99565-99581, 2020

[8] A. A. M. Saleh and R. Valenzuela, "A Statistical Model for Indoor Multipath Propagation," *IEEE Journal on Selected Areas in Communications*, vol. 5, no. 2, pp. 128-137, Feb. 1987.

[9] C. Han, A. O. Bicen, and I. F. Akyildiz, "Multi-ray channel modeling and wideband characterization for wireless communications in the terahertz band," *IEEE Transactions on Wireless Communications*, vol. 14, no. 5, pp. 2402-2412, May. 2015.

[10] S. Li, W. Zhang, Y. Cui, H. V. Cheng and W. Yu, "Joint Design of Measurement Matrix and Sparse Support Recovery Method via Deep Auto-Encoder," *IEEE Signal Processing Letters*, vol. 26, no. 12, pp. 1778-1782, Dec. 2019